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Determination of Nearshore Sandbar Crest Depth Using Neural Network Approach

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Abstract— *For the coastal structure designs, nearshore sandbars are crucial since they are affected highly from various parameters like beach slope, the height and period of the wave and the properties of the material forming the bed. In this study, it was investigated the sediment movements in nearshore by using various bar crest depths and a physical model. Erosion profile output is used for determination of the bar crest depths. Linear and non-linear regression methods are used for obtaining the non-dimensional equations with the experimental data. These equations are then compared with the ones found in the literature. Transportation of on-off shore sediments is affected by bar crest depth which has been examined with the materials forming the beach by using various diameter of the medium as d_{50}=0.25, 0.32, 0.45, 0.62 and 0.80 mm. In order to estimate nearshore sandbar crest depth, we have developed an approach by using neural network (ANN). For proposing the efficiency of the study, ANN and multi-nonlinear regression models are compared with each other.*

Keywords— Nearshore Sandbar, Crest depth, Artificial neural network, Multi-nonlinear regression, Experimental study.

I. INTRODUCTION

In coastal management, performing a study about the coastal zone and the phases leading to the morphological behaviors of the sandbars is crucial. In terms of wave action, circulation as a result of the currents, sediment movements on the bottom of the ocean and the interaction of them all, the nearshore environment is quite complex and dynamic.

Models of the nearshore constructed using knowledge of physical processes are common in physical geography, civil engineering and coastal oceanography [1]. The generation and evolution of nearshore sandbars have investigated for several decades. Field and laboratory studies have carried out in order to observe bar formation and migration events. Cambazoglu [2] predicted offshore bar migration and onshore bar migration events on storm time-scales. Larson and Kraus [3], suggested an equation for bar crest depth using experimental data as well as for erosion and deposition criteria. Proposed formula for bar crest depth is given in Table 1. Silvester and Hsu [4], studied beach profile parameters using non-linear regression techniques. In this study, the proposed formula for bar crest depth is given in Table 1. Larson [6], studied cross-shore sediment transport and the beach profile under effects of regular waves and a numerical model was proposed. Hsu [7], determined the geometry of offshore bar. He concluded that cross-shore waves traveling with variable angles make the beach profile be in equilibrium. Günaydın and Kabdaşlı [8], carried out experimental models to investigate the geometric characteristics of offshore bars. Some empirical expressions were proposed using regular waves, irregular waves and regular-irregular waves. Proposed equation for bar crest depth is given Table 1. Kömürcü at al. [9], studied cross-shore sediment transport by carrying out laboratory experiments. Equations were generated for bar parameter by using regression analysis. Bar crest depth and corresponding equation (Eq. (4)) is given in Table 1. Özölçer [10], studied geometric characteristics of erosion profile in a wave flume using regular waves. The results showed that the experimental data fitted well to the proposed equations with respect to the previously developed equations. Demirci and Aköz [11], conducted an experimental study to investigate the geometrical characteristics of beach profiles under storm conditions and the parameters affecting on-off shore sediment transport for the different beach materials. Demirci and Aköz [12], investigated bar parameters occurred by cross-shore sediment transport and proposed nondimensional equations for bar parameters. Demirci et al. [13], investigated cross-shore sandbar volumes and Demirci et al. [14], also predicted proposed nondimensional equations for bar volumes.

Recently, the application of ANN technique in ocean and coastal engineering has increased rapidly. Whereas there are a few ANN applications with sediment transport (Pape et al. [15]; Sing et al. [16]; Kömürcü et al. [17],; Kankal et al. [18]).

In this study, experiments were carried out for investigating near shore bar crest depth and non-dimensional equations for sandbar crest depth was generated by using linear and nonlinear regression methods. A neural network approach was also proposed to estimate nearshore sandbar crest depth.

Table.1: Currently used equations for determination of bar crest depth

Authors	**Bar Crest Depth Equation**	**Eq. no**
Larson and Kraus (1989)	$h_t = 0.66H$	(1)
Silvester and Hsu (1997)	$h_t / L_0 \tan\beta = 0.0269 + 0,391(X_t / L_0)$	(2)
Günaydın and Kapdaşlı (2005)	$h_t = 3.2041(\tan\beta\sqrt{(H / L_0)}^{1.413} L_0$	(3)
Kömürcü et al. (2007)	$h_t = 0.0101 m^{-0.6489} T^{0.8542} H_0^{0.6807} d_{50}^{-0.2267}$	(4)

Where H_0 is deep water wave height, L_0 is deep water wave length, $\tan\beta$ is bottom slope, d_{50} is grain size, X_t ishorizontal distance between the final bar point and the original shoreline

II. METHODS

In the present study, experiments results were used to investigate near shore sandbar crest depth in a wave channel of 12m in length, 0.40 m in width and 0.60 m in depth. (Figure 1). Three different beach slopes were used and values of these slopes both represent slopes in nature and make laboratory conditions easy. Beach slopes were 1/8, 1/10 and 1/15, respectively. Regular waves were conducted between 7-14 cm high for period between 0.47 and 0.83 s. In this study, five different materials in which, mean diameters (d_{50}) are 0.25, 0.32, 0.46, 0.62 and 0.80mm were used.

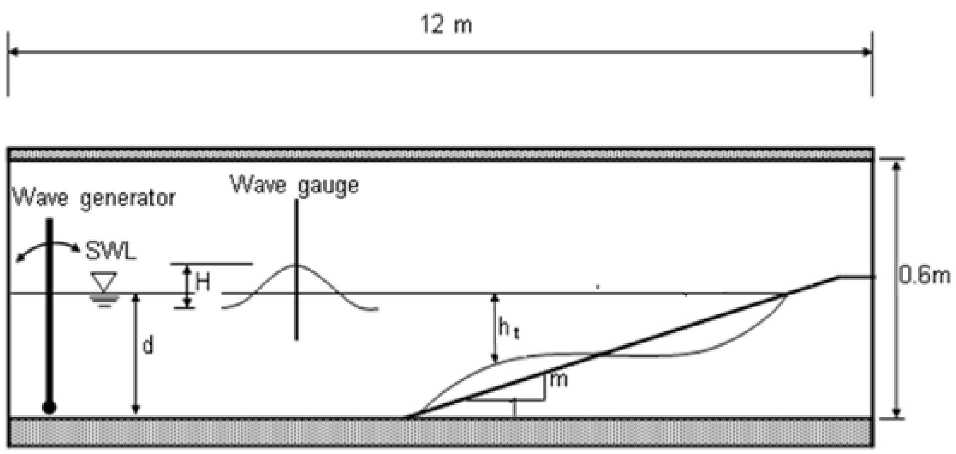

Fig.1: Wave Channel and Experimental Parameters

In the figure 1, h_t is vertical distance between the bar crest and the SWL, H is the wave height, d is the water depth, still-water level (SWL).

2.1 Multi-linear (MLR) and Multi-nonlinear Regression (MNLR) Model and Model Structures

Analysis method of experimental results

Experimental results were investigated using linear and non-linear regression methods to obtain equations defining the bar crest depths. Power (PF) and linear (LF) equations were generated in regression analyses. These functions are given respectively as follows:

$$y_0 = b_0 x_1^{b1} x_2^{b2} x_3^{b3} x_4^{b4} .....x_n^{bn} \quad (5)$$

$$y_o = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + ... + b_n x_n \quad (6)$$

Experimental results were examined in detail and used to obtain the fittest equations containing bar crest depth using linear and non-linear regression method. Different regression analyses were applied on bar crest depth.

Dimensional and non-dimensional variables

In this study, non-dimensional bar crest depths were used for estimation process. h_t was considered as an independent variable and was obtained from dividing by L_0 , H_0 and d_{50}. In constructing non-dimensional equations, independent variables, m, H_0/L_0, H_0/d_{50} and H_0/wT were used in various combinations, in final expression w is the velocity of fall.

2.2 . Artificial Neural Networks (ANN) and ANN Model Structure

Parallel information of the Brain's architecture is used to derive ANN approach which is a non-linear black box model. There is a growing interest on ANN models which have been studied widely and used in a wide range of complex problems including the large scale problems in many disciplines. ANNs do not depend on the complexity or the structure of the phenomenon which can be considered as an advantage of them comparing to the traditional methods. The main characteristics of ANN can be listed as it is capable of learning from examples, recognizing the pattern from the data obtained from those examples and adapting the process information and the solutions quickly. Therefore, ANN method can be used for the problems having complex and non-linear water sources with high amount of inputs and boundary conditions. Recent studies show that with a limited experimental data, ANN has the ability to provide quite satisfactory estimations. Hence, ANN method based model is developed in this study to estimate the bar bar crest depths resulted by the transportation of cross-shore sediment.

In this study, we have used Multi Layer Perceptron (MLP) with Back-Propagation Algorithm (BPA) which can be considered as the most popular ANN architectures. For training MLP, Levenberg–Marquardt technique was used since it is more powerful and faster technique comparing to the conventional gradient descent technique (Haghan & Menaj [20]; El-Bakyr [21]; Cigizoglu & Kisi [22]). In order to create an optimum network, this technique finds the correct combination of weights and squared errors after minimizing their combination. On the other hand, MLP can present on more than one hidden layer. Computational complexity and generalization capability of the network topology is affected directly by the network topology which is why it is an important issue to determine an appropriate architecture for a particular problem (Markus et al. [23]; Cybenco, [24]; Hornik et al. [25]). The number of the layer/s and nodes have effective role on the network performance. Thus, in order to get the best network performance, optimum number of hidden layers and nodes are important. Any optimization technique including trial and error method can be used to achieve optimum architecture for the network. That is why, many ANN architectures were considered and their errors were investigated and it is found that a hidden layer with five nodes is adequate for modeling the input-output relationship. Fig.2 shows the ANN networks architecture we used in this proposed study. The network contains three layers and every neuron from a layer is connected to the one from the next layer. In the figure, the output variable is bar crest depth (ht), Wi j's are weights and Bm is the bias term. The inputs are "d_{50}" as sediment diameters, "m" as the bed slope, "T" as the time period, and "Ho/Lo" wave steepness.

Firstly, the observed data was clustered in two groups for ANN modeling. Total of 64 experimental measurements were made. 49 of them (approximately 77%) were used for training the model and the remaining measurements (approximately 23%) were used for model testing. All data both for training and testing sets were selected randomly. For ANN model application a Matlab code string was written. For Back-Propagation Algorithm the function, log-sigmoid is used and so the input and output variables should be normalized. In the ANN model, iteration number, learning and momentum rate are taken as 2000, 0.15 and 0.99, respectively.

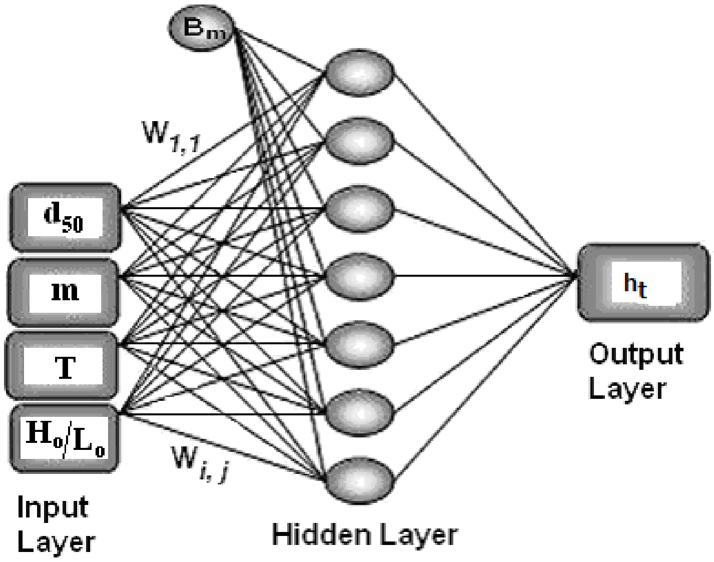

Fig. 2: Artificial Neural Network structure used in this study

For ANN modeling first, the observed data was arranged in two groups. 49 of 64 experimental measurements (approximately 77%) were used for training the model and the remaining 15 experimental measurements (approximately 23%) were used for model testing. Both the training and testing data sets were randomly selected. MATLAB code is written for ANN model application. The log-sigmoid function is used for Back-Propagation Algorithm and so a normalization of the input and output variables needs to be done. In the ANN model, iteration number, learning and momentum rate are taken as 2000, 0.15 and 0.99, respectively.

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For each model, mean square error (MSE), mean absolute error (MAE) between model estimations and the observed values are computed as follows.

$$MSE = \frac{1}{N}\left(\sum_{i=1}^{N} Yi_{observed} - Yi_{forecast}\right)^2 \qquad (7)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Yi_{observed} - Yi_{forecast}\right| \qquad (8)$$

Where, N and Y_i denote the number of data sets, bar crest depth, respectively

III. ANALYSİS OF THE MODELS AND THEİR RESULTS

3.1 Prediction of Bar Crest Depth with the MLR and MNLR model

In this study, sandbar crest depths for 64 experiments were calculated. Non-dimensional equations were presented as a result of regression analyses. The determination coefficient for non-dimensional dependent and independent variable alternatives were conducted by non-dimensional regression techniques using various function types**.** The dimensionless dependent variables (h_t / L_0, h_t /d_{50}, h_t /H_0) and the independent (H_0/L_0, and H_0/d_{50}, H_0/wT) were implemented for all parameters. Table 2 shows determination coefficients for different dimensionless dependent and independent variables.

Table.2: Determination coefficients for dimensionless alternatives variables for h_t

Status of the dimensionless variables		For multi linear function	For multi nonlinear function
Dependent variable	Independent variable	R^2	R^2
h_t /L_0	$m, H_0/L_0, H_0/wT, H_0/d_{50}$	0.298	0.367
	$m, H_0/L_0, H_0/d_{50}$	0.257	0.333
	$m, H_0/d_{50}, H_0/wT$	0.178	0.270
h_t/H_0	$m, H_0/L_0, H_0/wT, H_0/d_{50}$	0.168	0.174
	$m, H_0/L_0, H_0/d_{50}$	0.104	0.090
	$m, H_0/d_{50}, H_0/wT$	0.131	0.108
h_t/d_{50}	$m, H_0/L_0, H_0/wT, H_0/d_{50}$	0.244	0.328
	$m, H_0/L_0, H_0/d_{50}$	0.194	0.260
	$m, H_0/d_{50}, H_0/wT$	0.217	0.275

It is also shown in Table 2 that if dependent variable is selected as h_t/L_0, and independent variables are selected as m, H_0/L_0, H_0/d_{50}, H_0/wT, the maximum value of determination coefficient for linear function occurs. For the multi-hyperbolic function, If dependent variable is selected as h_t/L_0, and independent variables are selected as m, H_0/L_0, H_0/d_{50}, H_0/wT, the maximum value of determination coefficient for linear function occurs.

Maximum values of the determination coefficient are shown in Table 3 for multi linear and nonlinear functions.

Table.3: Regression coefficients obtained from dimensionless regression analysis for h_t

Multi Linear Function		Multi Non-Linear Function	
$\frac{h_t}{L_0} = b_0 + b_1 m + b_2\frac{H_0}{L_0} + b_3\frac{H_0}{wT} + b_4\frac{H_0}{d_{50}}$		$\frac{h_t}{L_0} = b_0 m^{b_1}\left(\frac{H_0}{L_0}\right)^{b_2}\left(\frac{H_0}{wT}\right)^{b_3}\left(\frac{H_0}{d_{50}}\right)^{b_4}$	
R^2=0.298		R^2=0.367	
Coefficients	*Values*	Coefficients	Values
b_0	*0.047*	b_0	21.12
b_1	*0.285*	b_1	0.233
b_2	*0.941*	b_2	2.92
b_3	*-0.179*	b_3	-2.84
b_4	*0.009*	b_4	-0.091

It is shown in Table 3 that multi hyperbolic functions give better results according to the multi linear functions. The generated equation for dimensionless hyperbolic functions is presented below for bar crest depths.

$$\frac{h_t}{L_0} = 21.12 m^{0.233} \left(\frac{H_0}{L_0}\right)^{2.92} \left(\frac{H_0}{wT}\right)^{-2.84} \left(\frac{H_0}{d_{50}}\right)^{-0.091} \quad (9)$$

In the Fig.3, the scatter plot for bar crest depth provides a high deviation for prediction. This deviation shows that the present MNLR model for raw data gives poor relationship between input and output parameters. The MNLR predicted and experimental measurements for bar crest depth are also given in Fig.3.

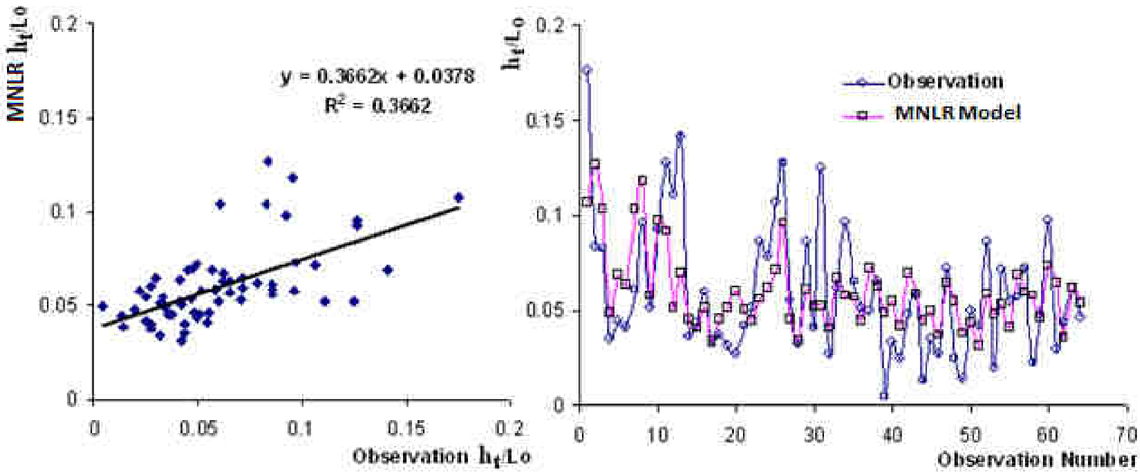

Fig. 3: MNLR model predictions compared with sandbar crest depth

3.2 Prediction of Bar Crest Depth with the ANN model

The most common learning procedure (BPA) for MLP is used for a set of input-output data in this study. A feed-forward Marquardt–back-propagation algorithm is implemented by developing a MATLAB code. Several ANN models are applied with different number of hidden nodes. One-hidden layer MLP model with four nodes and one output neuron is chosen for predicting bar crest depth.

Each model performances are calculated including the lowest mean square error (MSE), mean absolute error (MAE) and the highest coefficient of determination (R^2) between ANN, MLR and predictions of previous study and the observed experimental values. The statistical analyses are given Table 4, which shows the MSE, MAE and coefficient of determination (R^2) for testing period.

Table.4: Comparing performances of models created for the bar crest depth

Method	MSE (mm)	MAE (mm)	R^2
MNLR	289.413	13.038	0.366
ANN	67.703	6.088	0.934
Silvester and Hsu (1997)	366,225	16,555	0.4775
Larson and Kraus (1989)	1639.624	35.03	0.0086
Kömürcü et al. (2007)	1186.066	29.880	0.0314
Günaydın and Kapdaşlı (2005)	508.475	17.485	0.0097

MSE: Mean square error; MAE: Mean absolute error; R^2 :Determination coefficient

The ANN (4-hidden-node) model gives small MSE value for training and test data (see Table 4). ANN models also provides the lowest MSE (67.703 mm), MAE (6.088 m.), and the highest R^2 (0.934) for testing data.

Better results can be obtained by using ANN method rather than MLR method. Fig.4 presents ANN predictions for the testing period. It can be concluded from the figures that good predictions can be obtained from ANN models during the phases of data testing. It can be concluded from these figures that the ANN model estimations are less scattered which result in lower MSE, MAE and higher R^2 values than other models. Shore bar crest depth variation has nonlinear and unsteady conditions which is why the ANN model provides the best performance correlations for test data sets.

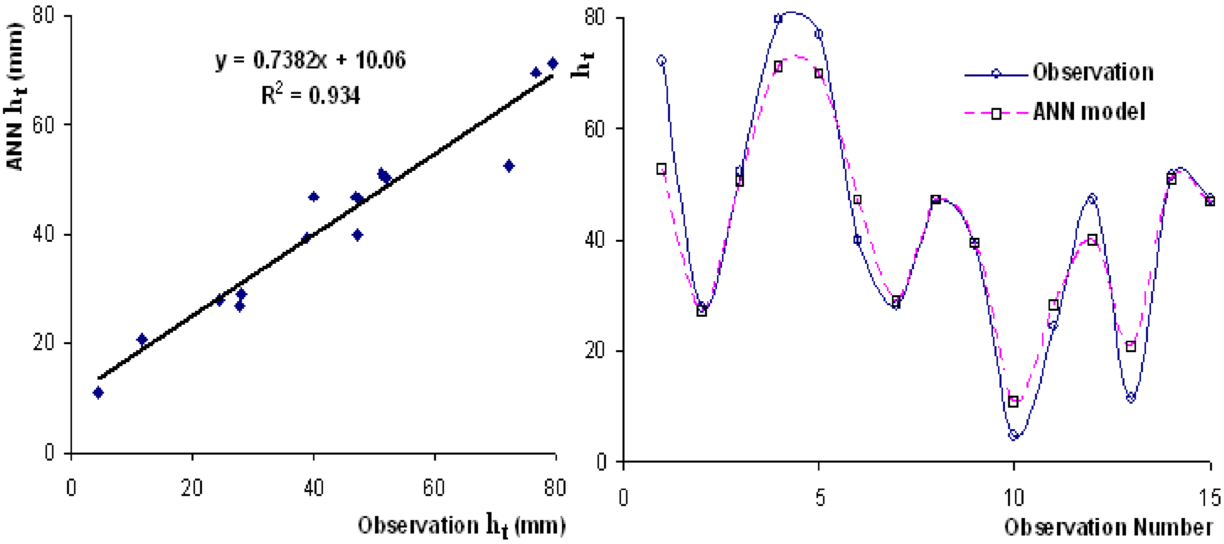

Fig. 4: ANN model predictions compared with sandbar crest depth in the testing period

The measurements for the performance evaluation were also carried out for the previous models which include mean absolute error (MAE), the mean square error (MSE) and determination coefficient (R^2). If we compare this study with the previous ones, the scatter plots for bar crest depth shown in the Fig.5 provides a higher deviation for prediction. One can see from Fig. 5 that the previous model estimates (Larson and Kraus [2], Silvester and Hsu [3], Kömürcü et al. [17]) are high scattered resulting in higher MSE, MAE and lower R^2 values than ANN and MLR models.

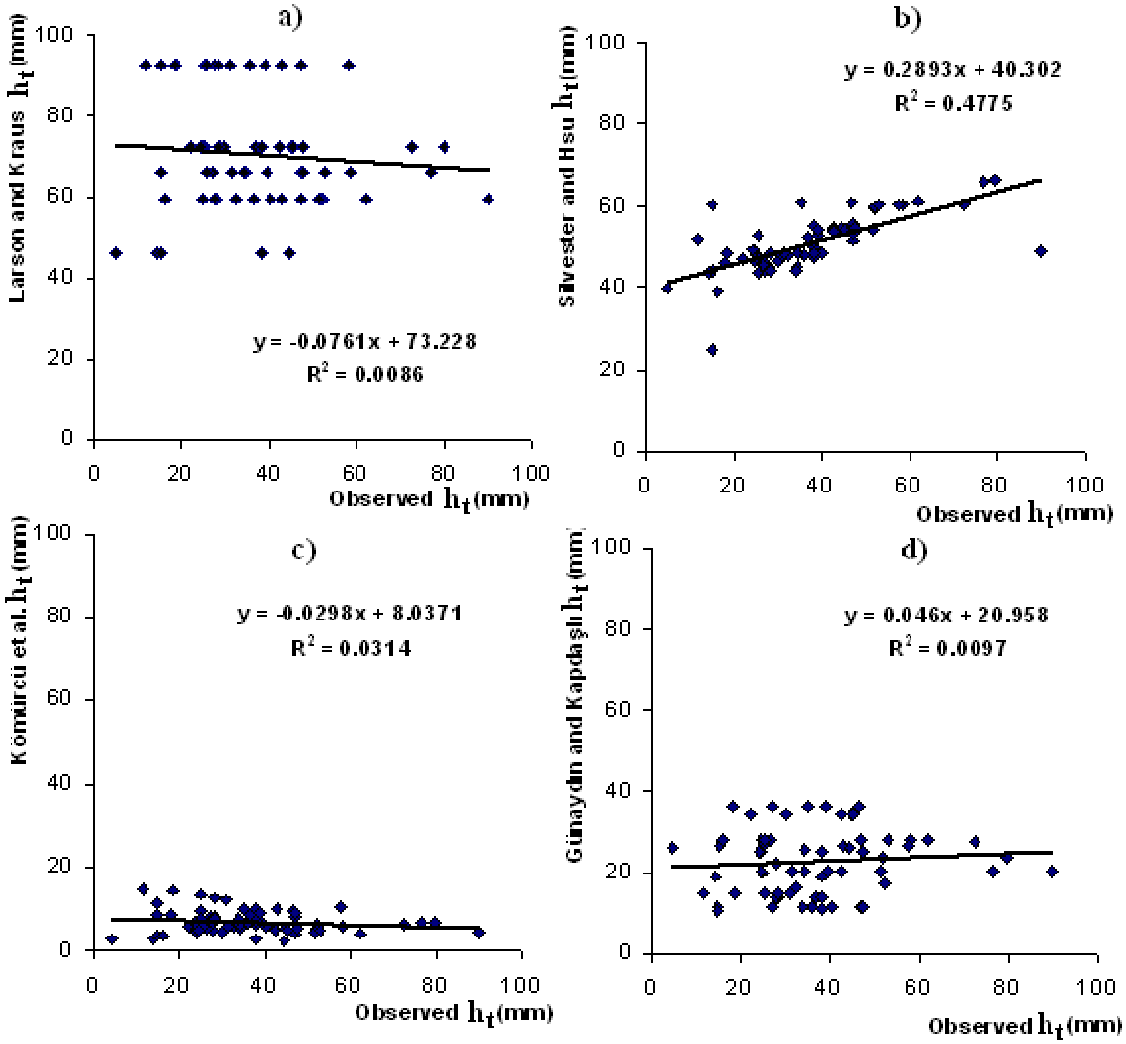

Fig. 5: Previous studies scatter graph for the observed sandbar crest depth

Comparison of bar crest depth (h_t) with the previous studies

Fig. 6 shows the comparison of the equations developed previously with each other in terms of our experimental results for bar crest depth (h_t). Even though there are some deviations with respect to the other equations, Silvester and Hsu's equation (Eq. (2)) illustrates similar trends with the our experimental results. Gunaydin and Kapdasli's equation (Eq. (3)) are close to our experimental results and developed equation (Eq. (9)). According to the experimental results and other equations, Larson and Kraus's equation (Eq. (1)) and Kömürcü et al.'s equation (Eq.(4)) gives quite different results.

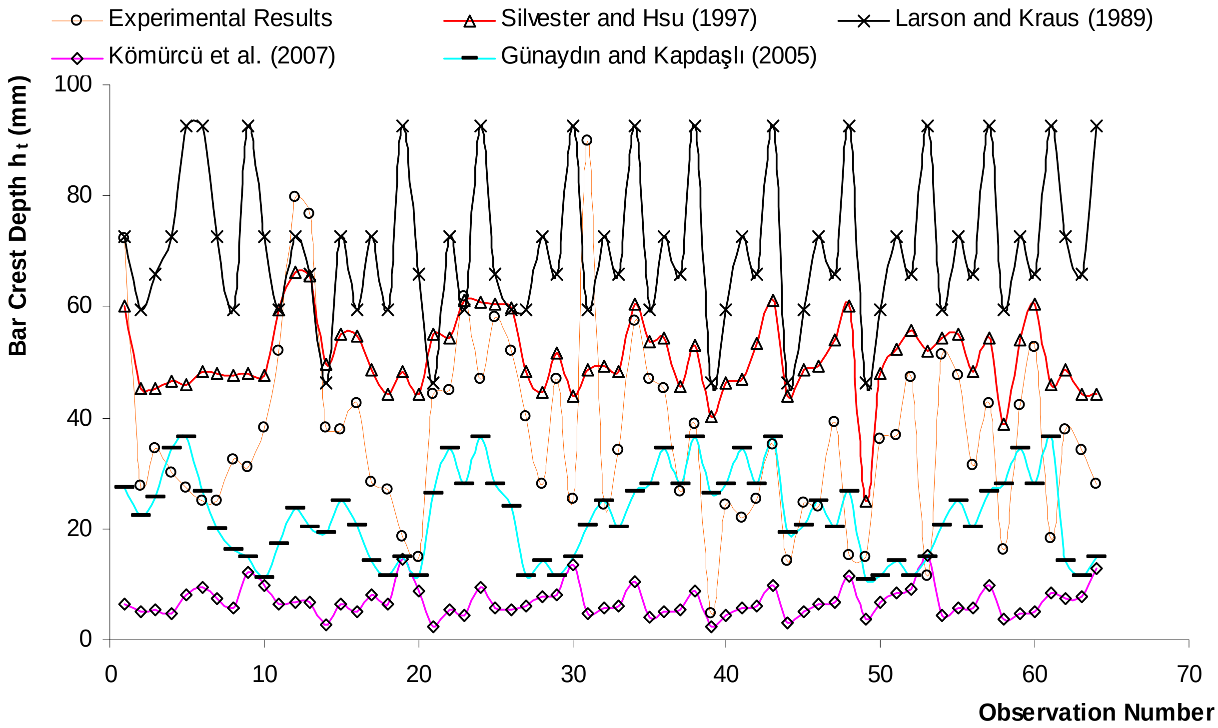

Fig. 6: Comparison of the experimental results and equations for sandbar crest depth

IV. CONCLUSIONS

In this study, sandbar crest depth (h_t) was investigated by using the results obtained from 64 experiments. Nondimensional equations were generated by applying linear and nonlinear regression methods. These equations were compared with the ones in the literature.

According to the regression analysis results, Equation (9), provides good fit Silvester and Hsu's equation. Equation (9) is also closer to experimental results. Silvester and Hsu's equation gives best results according to the experimental results and proposed equations. Larson and Kraus's, Kömürcü et al. and Günaydın and Kapdaşlı's equations doesn't provide good fit with the other equaitons.

The presented ANN model provides better estimates for the sandbar crest depth than the other models. The accuracy of the ANN model in bar crest depth estimation was investigated and results were compared with the regression and the other models. Comparisons revealed that the ANN model had the best accuracy in bar crest depth estimation.

As a result, the ANN approach can be used for estimation of sandbar crest depth. This is also verified that the ANN can produce outstanding results with respect to most well-known deterministic methods in terms of estimation of unknown coefficients, even number of variables are greater than five variables.

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